MFPT

James P. Hofmeister, a member of the Board of Directors of the Society for Machinery Failure Prevention Technology (MFPT) is a co-author of a new Wiley book, Prognostics and Health Management: A Practical Approach to Improving System Reliability Using Condition-Based Data, that is included in the Wiley Series in Quality and Reliability Engineering. The series aims to provide a solid educational foundation for both practioners and researchers in the Q & R field to expand the reader's knowledge base to include the latest developments in this field. The series will provide a lasting and positive contribution to the teaching and practice of engineering. Dr. Andre Kleyner, Senior Editor of the Wiley series, described the new book.

As quality and reliability science evolves, it reflects the trends and transformations of the technologies it supports. A device utilizing a new technology, whether it be a solar power panel, a stealth aircraft, or a state-of-the-art medical device, needs to function properly and without failure throughout its mission life.

In addition to addressing the reliability of new technology, the field of quality and reliability engineering has been going through its own evolution, developing new techniques and methodologies aimed at process improvement and reduction in the number of design- and manufacturing-related failures. One of these disciplines is prognostics and health management/monitoring (PHM), a fast-growing field that injects a more proactive approach into system reliability, where application of physics of failure (PoF), degradation analysis, and modern algorithms allow the prediction of failure time and, consequently, the ability to take actions preventing failures from happening. Safety standards, along with the fast development of autonomous vehicles, increases the pressure to achieve exceptionally high system reliability, thus making PHM an indispensable tool to meet these expectations and provide many advantages to users and maintainers, including financial benefits such as operational and maintenance cost reductions and extended lifetime. Despite the additional cost required to facilitate prognostics, PHM has positive effects on the overall lifecycle cost of the system by avoiding costly and sometimes catastrophic failures.

This book has been written by the leading experts and state-of-the-art practitioners in the field of prognostics and health management/monitoring. It discusses the many technical aspects of PHM along with its cost benefits and will be an excellent addition to this book series. Quality and reliability education is paradoxically lacking in today's engineering curriculum. Few engineering schools offer degree programs or even a sufficient variety of courses in quality or reliability methods. Therefore, the majority of quality and reliability practitioners receive their professional training from colleagues, professional seminars, publications, and technical books. The lack of formal education opportunities in this field greatly emphasizes the importance of technical publications for professional development.

This book, as well as the whole series, continues Wiley's tradition of excellence in technical publishing and provide a lasting and positive contribution to the teaching and practice of engineering.

Mr. Hofmeister writes: A prognostics and health management/monitoring (PHM) system can be thought of as consisting of three major systems: (1) a sensing system consisting of a sensor and a feature vector framework, (2) a prognosis system comprising a prediction framework and a performance-validation framework, and (3) a health-management framework. Although health management is probably the most complex and most expensive, the book presents topics related to sensing systems and prognosis to provide accurate prognostic information regarding the prognosis of the health of the system being monitored.

Presented in the book are approaches to reliability predictions based on traditional model-driven, data-driven, and hybrid-driven methods. Those traditional, or handbook, methods are evaluated as inaccurate and misleading when used for prognostic estimation of a future failure. Next, the book develops approaches to modeling and data handling that take into account failure modes and operational environment and conditions and presents an approach using signatures created by extracting leading indicators of failure/condition indicators as feature data that forms condition-based data (CBD) signatures; such signatures can be normalized and converted into dimensionless ratios called fault-to-failure progression (FFP) signatures. FFP signatures form families of characteristic curves, and each family of such curves is dependent on the totality of the mechanisms of failures causing degradation, resulting in changes in monitored signals.

A set of degradation signature models is developed, each model representing a single mode of degradation; and it is shown how those models can be used to transform FFP signatures into degradation-progression signature (DPS) data that can then be transformed into functional failure signature (FFS) data that is particularly amenable to processing by prediction algorithms. FFS data forms linearized transfer curves with values of 0 or less in the absence of degradation and 100 or larger when the component, assembly, or system being monitored (a prognostic-enabled target) reaches or exceeds a level of degradation such that the prognostic target is no longer capable of operating within specifications. When all noise – defined as any change in data not due to degradation – is removed from monitored signals, an FFP signature can be transformed into DPS data that forms a linear straight-line transfer curve, which can be converted into FFS data by defining and using a threshold value that defines when functional failure occurs.

Since it is not practical to remove all noise, some useful signal-conditioning techniques are presented. Those techniques ameliorate and/or mitigate the effects of noise, including, but not limited to, the following: data fusion, data transforms, domain transforms, filtering, threshold margins, data smoothing, and data trending. Techniques are illustrated using example sets of noisy data, including those that exhibit signal variations and changes in the shapes of curves caused by the effects of temperature and feedback.

The book also presents the effects of nonlinear rates of degradation and multiple modes of degradation and methods and techniques for handling those effects. A heuristic-based approach to using degradation models and data conditioning is presented. It is shown that despite not knowing, for example, the exact value of the power for a power-function type of degradation or life value for an exponential-function type of degradation; or not knowing that the CBD signature is the result of an exponential rate of change in the degradation rate of an underlying power-function type of degradation; the FFS data becomes sufficiently linear to result in very accurate prognostic information.

Insufficient accuracy (errors) of prognostic information is caused by and/or due to insufficiency in the sensing system, primarily due to two factors: (i) the signal-conditioning and data-handling routines to fuse, transform, condition, and process data; and (ii) the use of insufficient rates of system sampling and data sampling (inexact modeling). It is asserted that, given sufficiently high system-sampling rates and data-sampling rates, the accuracy of prognostic information approaches a level limited by the system. System limits on prognostic accuracy are due to measurement uncertainty and errors: for example, digitization, quantization errors, mathematical rounding, manufacturing tolerances, variations in measurement values of environmental effects such as temperature and pressure, variations in values due to manufacturing, and so on.

An often-ignored contributor to prognostic accuracy/inaccuracy is the sampling method employed by the sensing system: it does not make sense to require a minimum prediction horizon for functional failure of 20 weeks within 10% accuracy and a time-of-failure precision of ±1 week from a sensing system that samples a node to acquire data once every 2 weeks.

It is shown that despite the effects of noise-induced nonlinearity of the transfer curves, the design and development of prediction algorithms for PHM systems is fairly straightforward and not very complex, and easily produces very accurate prognostic information such as estimates of remaining useful life (RUL) and state of health (SoH). For illustration, the authors use computational prediction algorithms incorporated in Adaptive Remaining Useful Life Estimator™ (ARULE™) programs.

A sensing system should acquire and manipulate CBD to sufficiently ameliorate and mitigate all noise using methods and means including sampling, filtering, masking, fusing, transforming of data types and domains such as time and frequency, smoothing, and so on. The ultimate goal of a sensing system used in a PHM system should be that of a transducer that transforms monitored signals into a sufficiently linear transfer curve to support producing accurate prognostic information. Prediction information should minimally contain the following:

- If the amplitude of the input is at or below a degradation threshold, health is 100%.
- If the amplitude of the input is at or above a failure threshold, health is 0%.
- Otherwise, the prognostic target is degraded: health is between 0% and 100%.
- RUL estimates: estimated time remaining before end of life (EOL) occurs.
- Prognostic horizon (PH) estimates: current time plus estimated RUL.

Included in the book is an exemplary design for a robust prototype of an exemplary PHM system comprising a framework architecture and control/data flow that supports prognostic enabling of six assemblies (line-replaceable units): two switch-mode power supplies and four electro-mechanical actuators.